Euclid Modelling Challenge

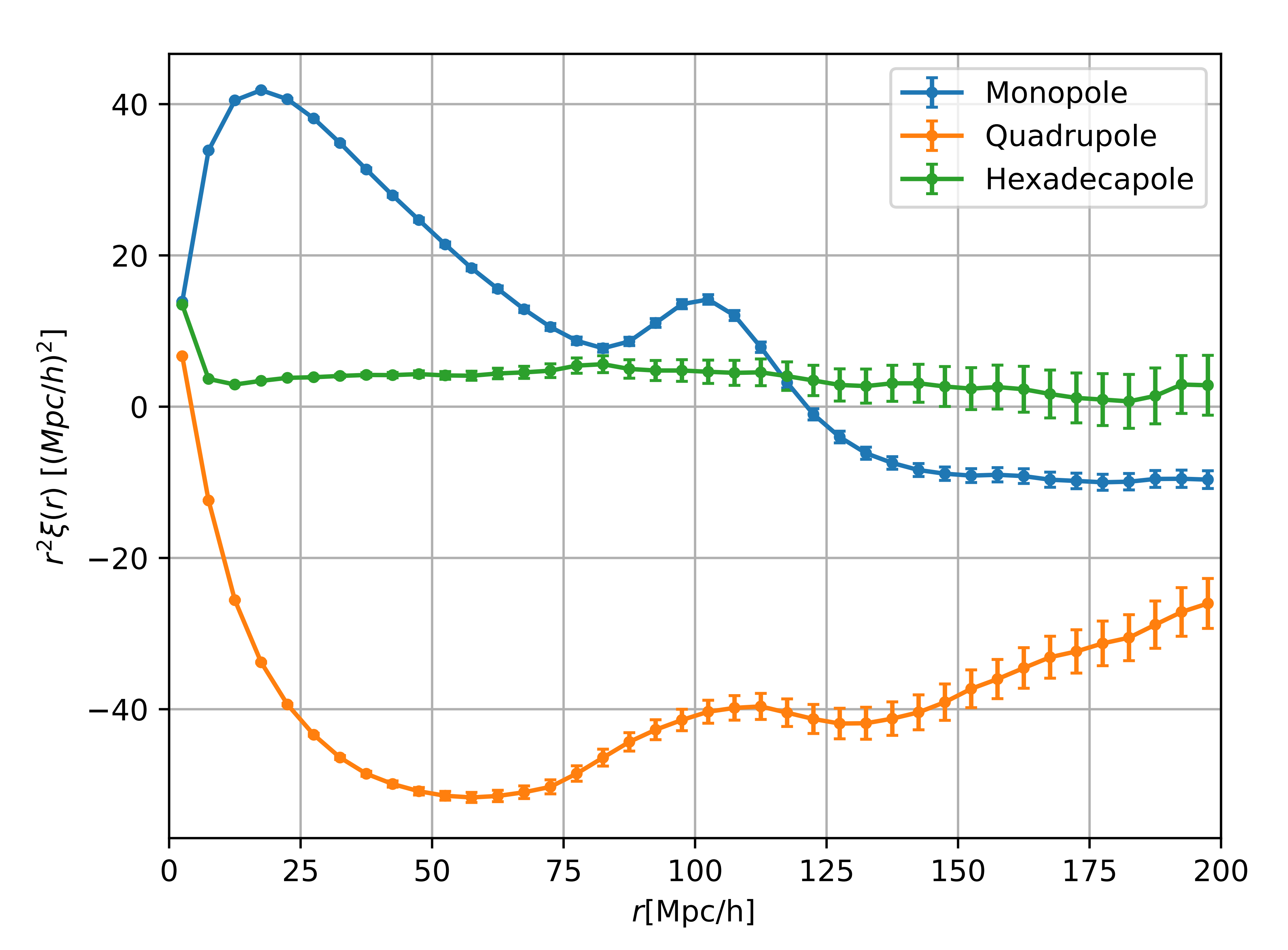
The 2PCF in Redshift-Space

Euclid France Clustering Meeting 2022 at LAM

Martin Kärcher, Sylvain de la Torre, Alfonso Veropalumbo, Michel-Andrés Breton

What is it about?

- Part of a whole suite of modelling challenges in the clustering SWG:
  - Power and bi-spectrum in real and redshift-space + combined analysis
  - 2PCF and 3PCF in real and redshift-space + combined analysis
- Different models for real to redshift-space conversion tested
- Try to recover growth parameter with 1% rel. accuracy → matching expected accuracy of Euclid
- Analysis done on same Euclid mock galaxy catalog throughout all challenges



Set the Stage for Modelling Challenge

- As simulation we use Flagship 1, HOD model 3 galaxies
- Average over three LOS and fit monopole, quadrupole and hexadecapole of ξ in redshift-space
- Four different redshifts z=0.9, 1.19, 1.53 and 1.79
- Three different minimum fitting lengths s_{min} = 20,30,40 Mpc/h
- Two codes for TNS model (SdlT, AV), one for CLPT (MAB) and one for CLEFT (SdlT)

The Models in more Detail

TNS (Taruya, Nishimichi, Saito)

- Start by exact expression for power spectrum in redshift space
- Expand the ensemble average in terms of cumulants
- Keep only terms up to specific order → two additional correction terms (A- and B-terms)
- Modelling completely done in Fourier space and then FFT'ed back to configuration space

$$\delta^{(\mathrm{S})}(\boldsymbol{k}) = \int d^3\boldsymbol{r} \left\{ \delta(\boldsymbol{r}) - \frac{\nabla_z v_z(\boldsymbol{r})}{a\,H(z)} \right\} e^{i(k\mu\, v_z/H + \boldsymbol{k}\cdot\boldsymbol{r})}$$

$$P^{(\mathrm{S})}(k,\mu) = D_{\mathrm{FoG}}[k\mu\, f\,\sigma_{\mathrm{v}}] \left\{ P_{\delta\delta}(k) + 2\,f\,\mu^2\,P_{\delta\theta}(k) + f^2\,\mu^4\,P_{\theta\theta}(k) + A(k,\mu) + B(k,\mu) \right\}$$

Taruya+ (2010)

The Models in more Detail

CLPT and CLEFT

- Gaussian streaming approximation for mapping from real to redshift space
- Real space modelling is done in CLPT (Convolutional Lagrangian Perturbation Theory) formalism based on the velocity moment generating function $Z(\mathbf{r}, \mathbf{J}) \rightarrow$ Wang+ (2013)
- Three main ingredients: correlation function in real space, mean pairwise velocity, velocity dispersion
- If ingredients are computed from LEFT (Lagrangian Effective Field Theory) $\rightarrow$ additional counter-terms $\rightarrow$ CLEFT model $\rightarrow$ Vlah+ (2016)
    - We keep three terms as free fit parameters

$$1 + \xi^s(s_\perp, s_\parallel) = \int \frac{dy}{\sqrt{2\pi}\,\sigma_{12}} [1 + \xi] \exp\left\{ -\frac{[s_\parallel - y - \mu v_{12}]^2}{2\sigma_{12}^2} \right\}$$

$$Z(\boldsymbol{r}, \boldsymbol{J}) = \int \mathrm{d}^3 q \int \frac{\mathrm{d}^3 k}{(2\pi)^3} \mathrm{e}^{\mathrm{i}\boldsymbol{k}\cdot(\boldsymbol{q}-\boldsymbol{r})} \int \frac{\mathrm{d}\lambda_1}{2\pi} \frac{\mathrm{d}\lambda_2}{2\pi} \times \tilde{F}(\lambda_1) \tilde{F}(\lambda_2) \left\langle \mathrm{e}^{\mathrm{i}(\lambda_1 \delta_1 + \lambda_2 \delta_2 + \boldsymbol{k}\cdot\boldsymbol{\Delta} + \boldsymbol{J}\cdot\dot{\boldsymbol{\Delta}}/H)} \right\rangle$$

Galaxy Biasing

- Renormalized bias up to one loop → 4 free bias parameters in TNS model
- Local Lagrangian (LL) approximation expresses two non-local bias parameters in terms of b_1 → 2 free bias parameters
- CLPT and CLEFT uses slightly different bias expansion → one additional free bias parameter in CLEFT

$$\delta_g = b_1\delta + \frac{b_2}{2}\delta^2 + b_{\mathcal{G}_2}\mathcal{G}_2 + b_{\Gamma_3}\Gamma_3$$

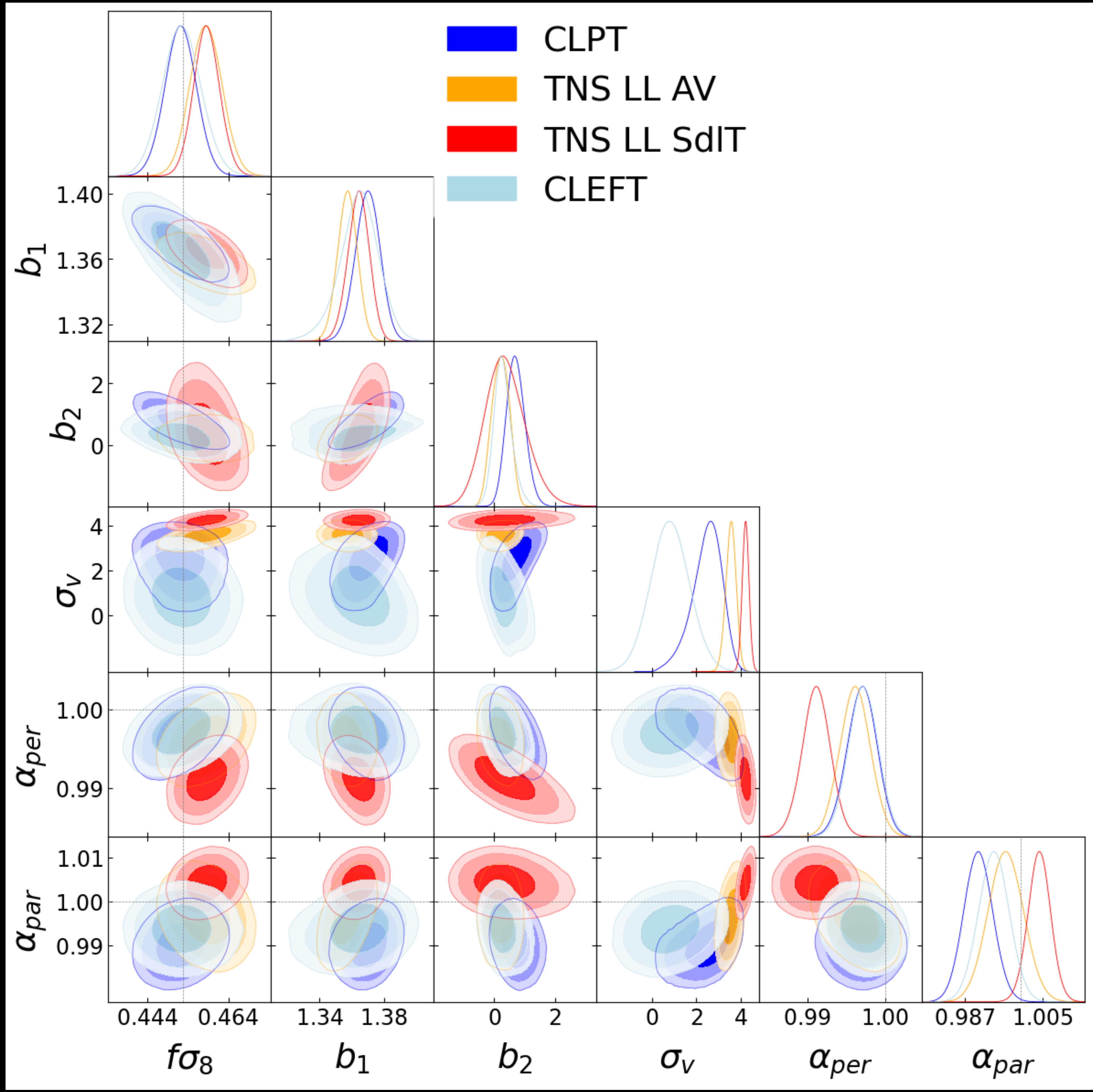
Bautista+ (2020)

$$b_{\mathcal{G}_2} = -\frac{2}{7}(b_1 - 1)$$

$$b_{\Gamma_3} = \frac{11}{42}(b_1 - 1).$$

Intermediate Results

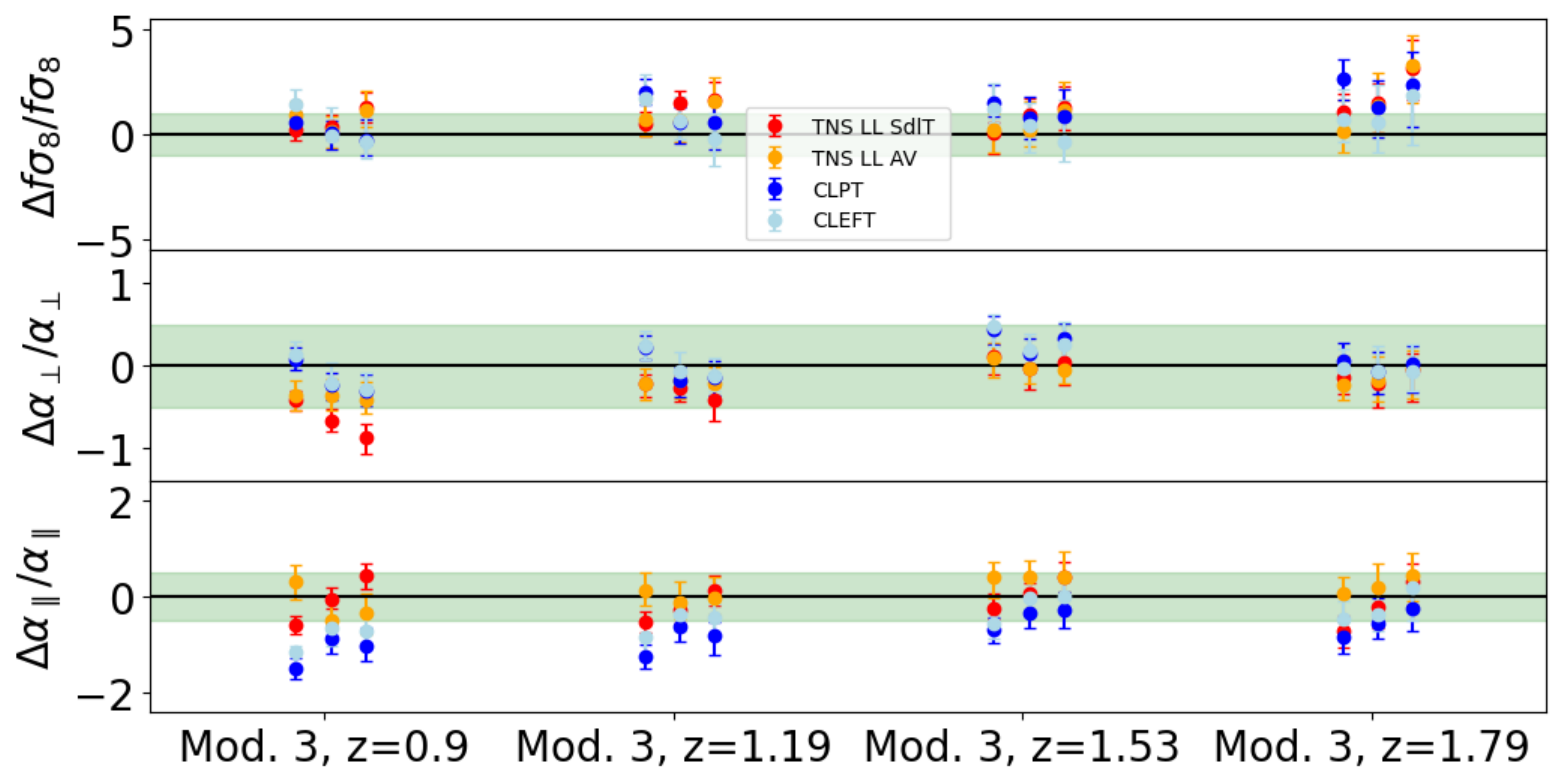
Contours



z = 0.9, s_{min} = 40 Mpc/h

Intermediate Results

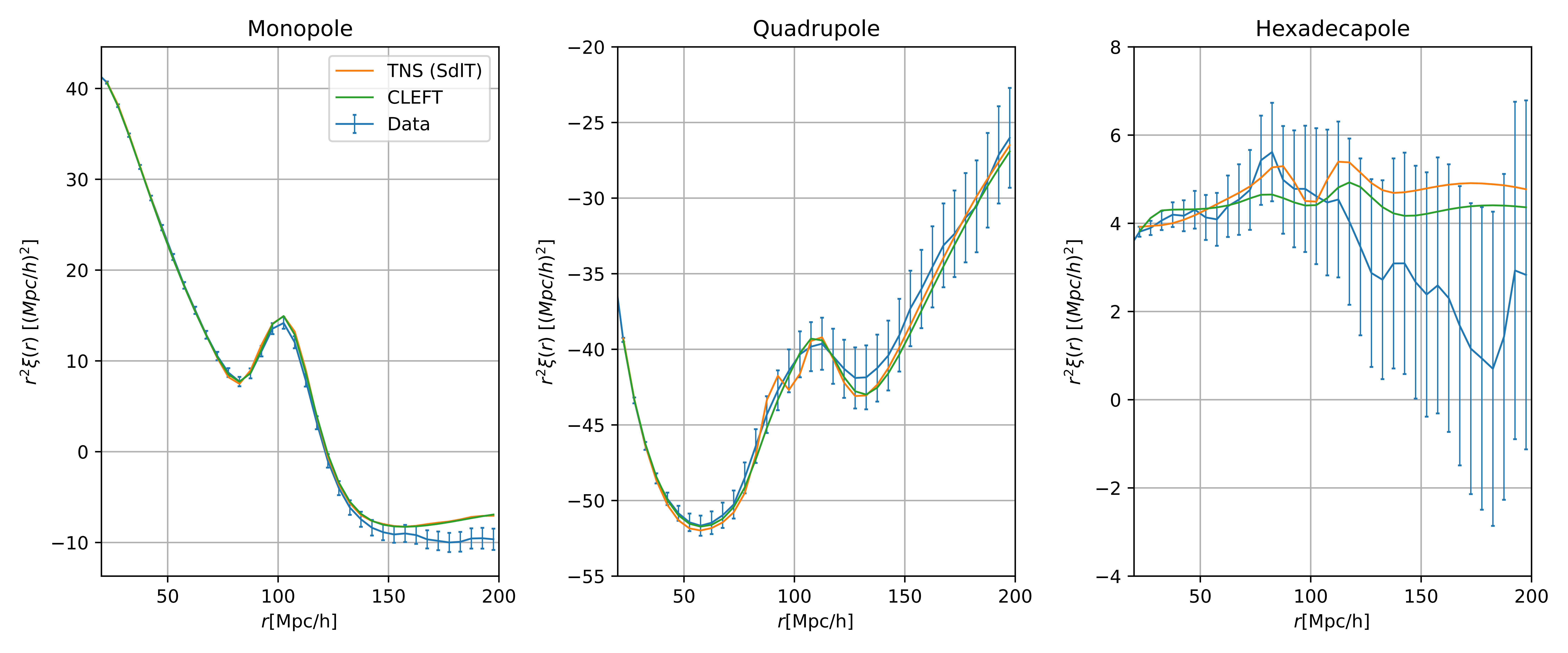
Best Fit Parameters



Relative difference in %

Intermediate Results

Best Fit Correlation Function



Assess Performance of the Models

- χ^2_{red} for best fit value → Over-/underfitting
- Figure of Merit (FoM) → Constraining power (Precision)
- Figure of Bias (FoB) → Recovery of fiducial parameters (Accuracy)

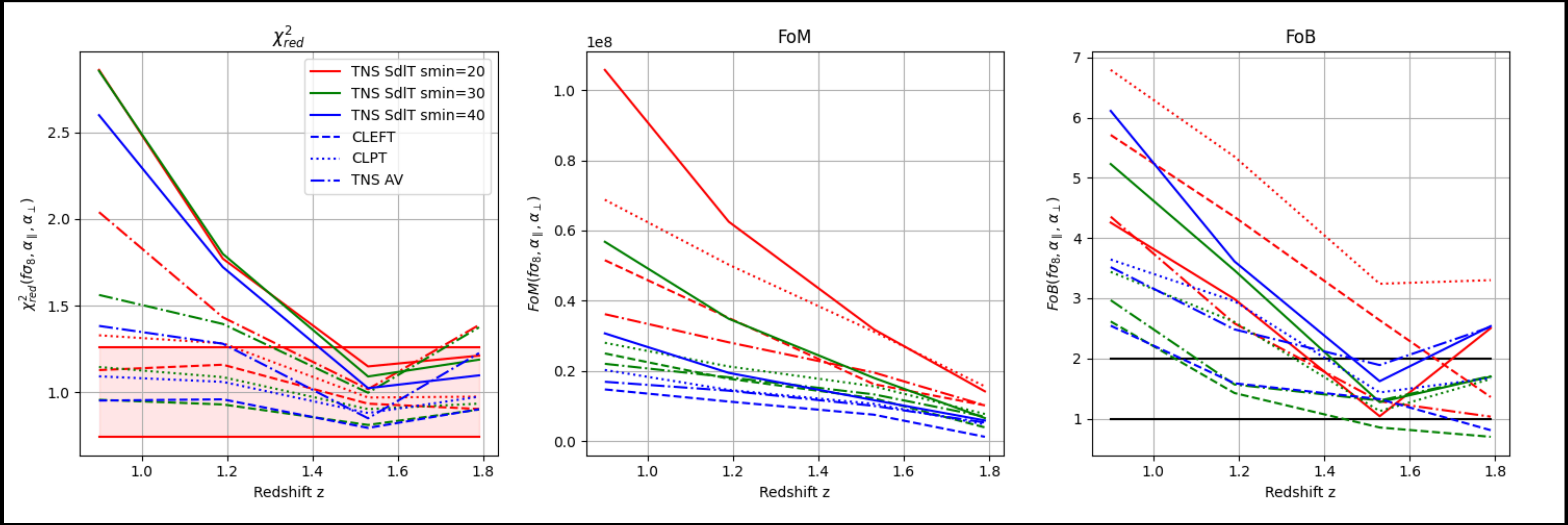
$$\mathrm{FoM} \equiv \frac{1}{\sqrt{\det\left[S_{\alpha\beta} / \left(\theta_{\mathrm{fid},\alpha}\, \theta_{\mathrm{fid},\beta}\right)\right]}}$$

$$\mathrm{FoB} \equiv \left[\sum_{\alpha,\beta} \left(\bar{\theta}_\alpha - \theta_{\mathrm{fid},\alpha}\right) S^{-1}_{\mathrm{tot},\alpha\beta} \left(\bar{\theta}_\beta - \theta_{\mathrm{fid},\beta}\right)\right]^{1/2}$$

Eggemeier+ 2021

Metrics computed for: $f\sigma_8, \alpha_{\|}$ and $\alpha_{\perp}$

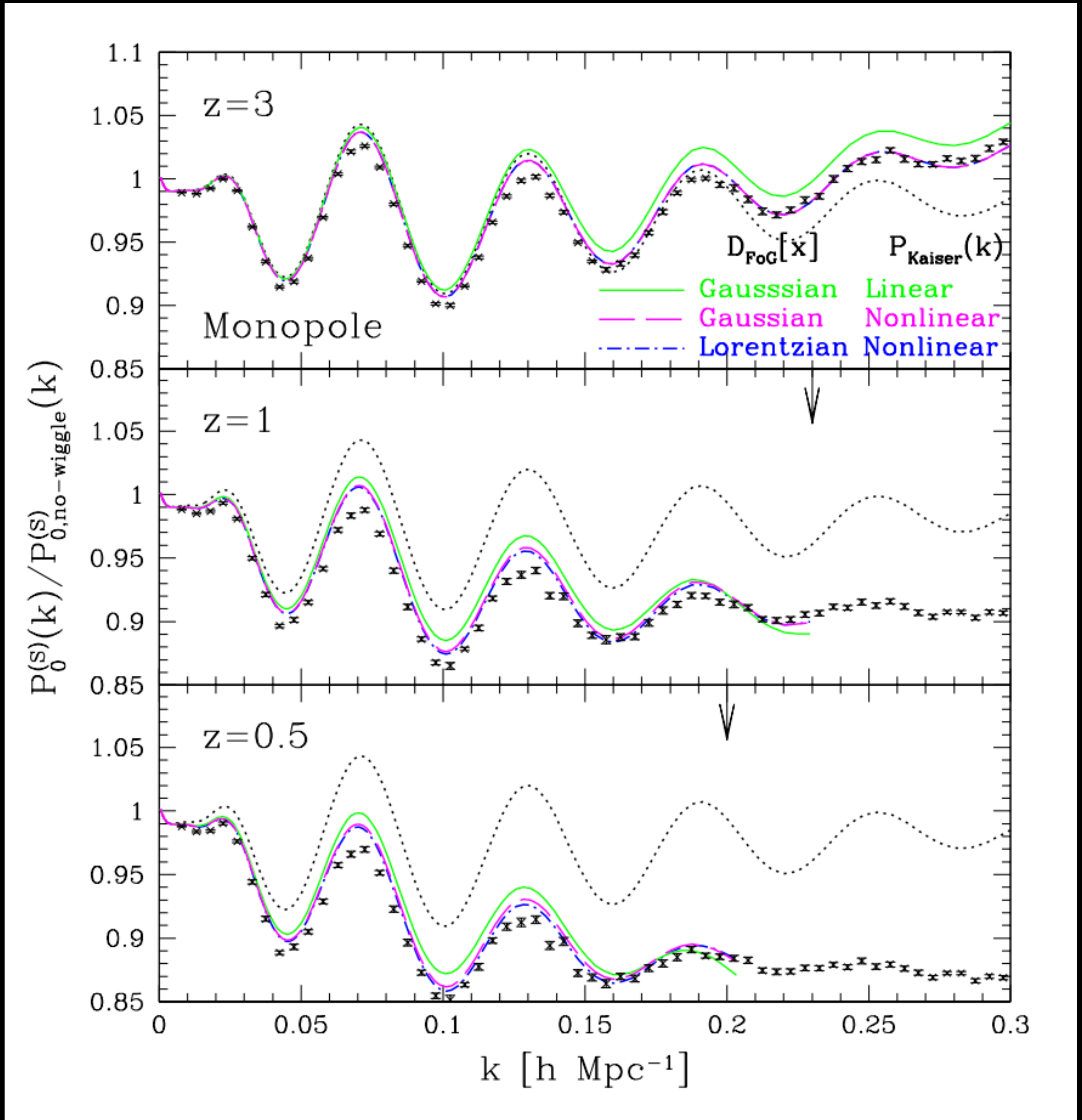
Assess Performance of the Models

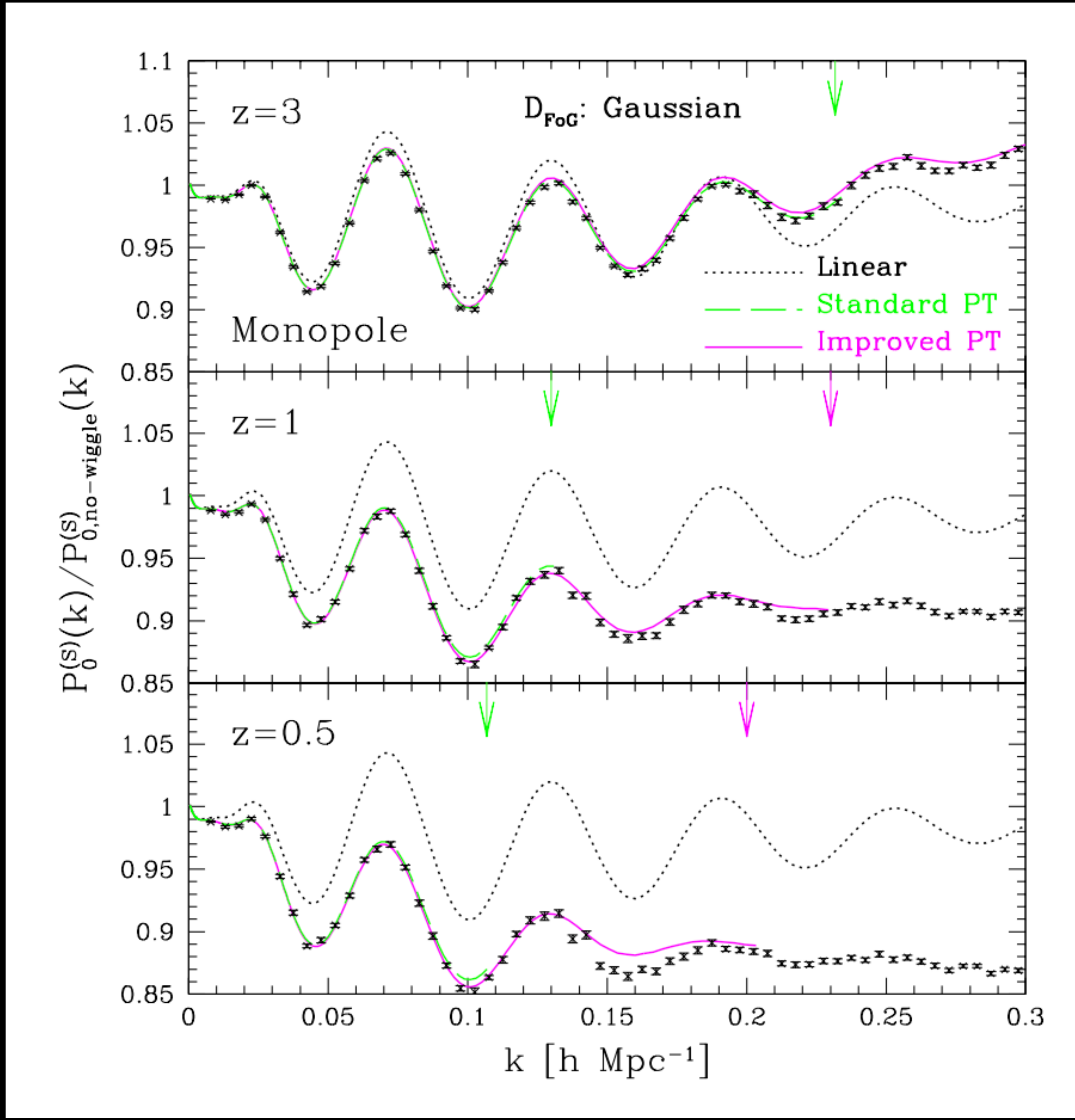


→ CLEFT and CLPT model seem to outperform the TNS implementations based on the χ^2_{red}

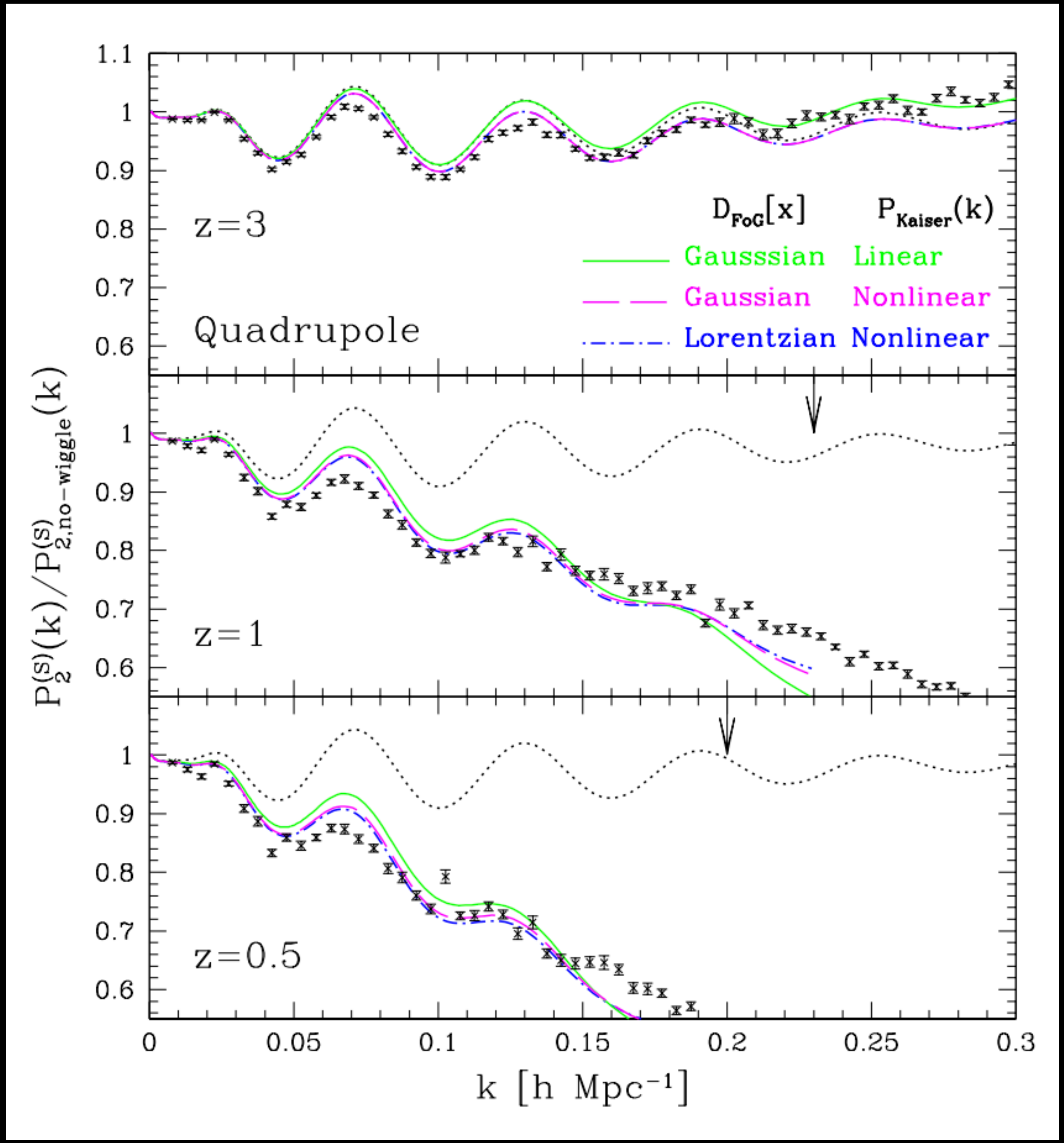
Future Prospects

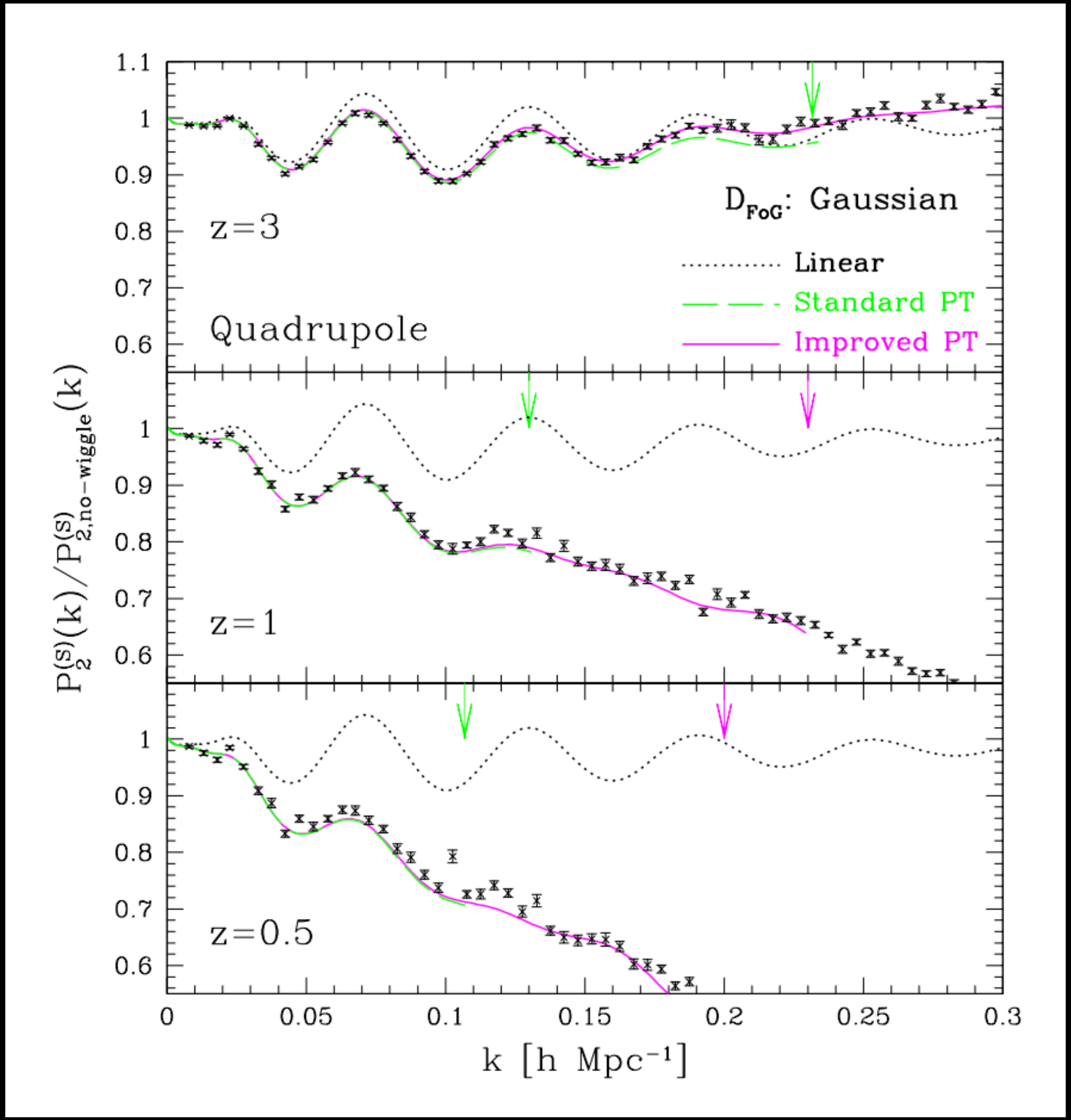
- In first comparison CLPT and CLEFT model seem to outperform TNS model
- Converge on one TNS implementation → Some discrepancies are currently investigated
- Explore different classes of models
  - TNS model with A-terms up to 2-loop order
  - CLEFT model from Fourier space (`Velocileptors` code)
- Once preliminary model comparison done → Full cosmological fit
  - Need of emulators as a new P_{lin} is needed for each likelihood evaluation
  - Correction terms (e.g. A- and B-terms in TNS) depend on P_{lin} and need to be emulated as well





Plots taken from Taruya+ (2010)





Plots taken from [Taruya+ (2010)]

Priors

TNS (SdIT)

f	[0.2 , 1.4]
b_1	[0.5 , 3.5]
b_2	[-10 , 10]
σ_v	[0 , 10]
$\alpha_{\parallel}$	[0.5 , 1.5]
$\alpha_{\perp}$	[0.5 , 1.5]

CLPT

f	[0 , 2]
b_1	[-0.5 , 3]
b_2	[-70 , 70]
σ_v^2	[0 , 100]
$\alpha_{\parallel}$	[0.5 , 1.5]
$\alpha_{\perp}$	[0.5 , 1.5]

CLEFT

f	[0.2 , 1.4]
$b_1 - 1$	[-0.5 , 2]
$2(b_2 - 4/21(b_1 - 1))$	[-10 , 10]
b_{s^2}	[-10 , 10]
α_ξ	[-20 , 100]
$10\alpha_v$	[-60 , 120]
α_σ	[0 , 100]
$\alpha_{\parallel}$	[0.5 , 1.5]
$\alpha_{\perp}$	[0.5 , 1.5]

Simulation Cosmology

Ω_m^0	Ω_c^0	Ω_b^0	h	n_s	A_s
0.319	0.27	0.049	0.67	0.96	2.11065×10^9